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A Customizable Simulation Model for Comprehensive Supply Chain Analysis

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1 INTRODUCTION

With their seminal work on the bullwhip effect in supply chains, Lee et al. paved the way for an extensive supply chain management discussion both in industry and academia [LePW97a; LePW97b]. With the development of the popular beer distribution game [Ster84] Sterman showed that locally optimal ordering decisions may lead to demand variance amplifications for upstream companies resulting in excess inventory and backorder costs for the entire supply chain [Ster89; Ster92]. To mitigate the inefficiencies, several collaboration concepts have been proposed in the literature. In particular, the concept of exchanging information with suppliers (demand data, inventory data, capacities, etc.) seemed to be a simple but effective way to reduce supply chain costs [cf. ZhXL02; TLFN03]. Much research has been done to study the effects of information sharing on the performance of the supply chain based on an analytical approach [cf. Chen98; GaKT99; CaFi00; LeST00; Ragu01; SiZh03]. However, the complexity of real supply chains is often too high to be modeled analytically.

With the rapid advances in information technology and the development of powerful commercial software tools, the analysis of supply chains by using simulation techniques became popular. The increasing power of software and hardware allows the analysis of rather complex supply chains including several stochastic elements [cf. CRGE98; WaJD99; MPLV02; SLAH03; AnNW04; CKHH04; LaHM04; ReRa05]. However, the simulation models are often not accessible. Strictly speaking, this is contrary to the main criterion of scientific work, namely the traceability and reproducibility of results. The descriptions of the model behavior in the published papers are often too imprecise and fuzzy, offering too much room for interpretation. Hence, a replication of existing simulation studies is often impossible [KnSR07].

The aim of this paper is to provide a comprehensible and credible supply chain simulation model that can be modified by the simulation user. The model allows the exploration of basic relationships in supply chains and provides insights into the complexity of supply chain simulation modeling. Through extensive analysis of output measures, the causality of effects may be better understood.

The remainder of this paper is organized as follows. Section 2 introduces the conceptual model and describes the functionality of the simulation model and its customization. In Section 3 the model is parameterized to obtain a valid base model for further experiments. Section 4 discusses the output of the base model for each supply chain member individually. In Section 5 certain input parameters such as demand distribution, order quantity, and lead time are modified to gain insights into causal relationships in the supply chain.

2 SUPPLY CHAIN SIMULATION MODEL

This section discusses the basic functionalities of the simulation model. First, the underlying theoretical model is presented. Second, the inputs and outputs of the simulation model are described and instructions for downloading and using the model are given.

2.1. Conceptual Model

2.1.1. Supply Chain Structure

The model is based on a divergent four-stage supply network consisting of a manufacturer, two distributors, four retailers, and twelve consumers.

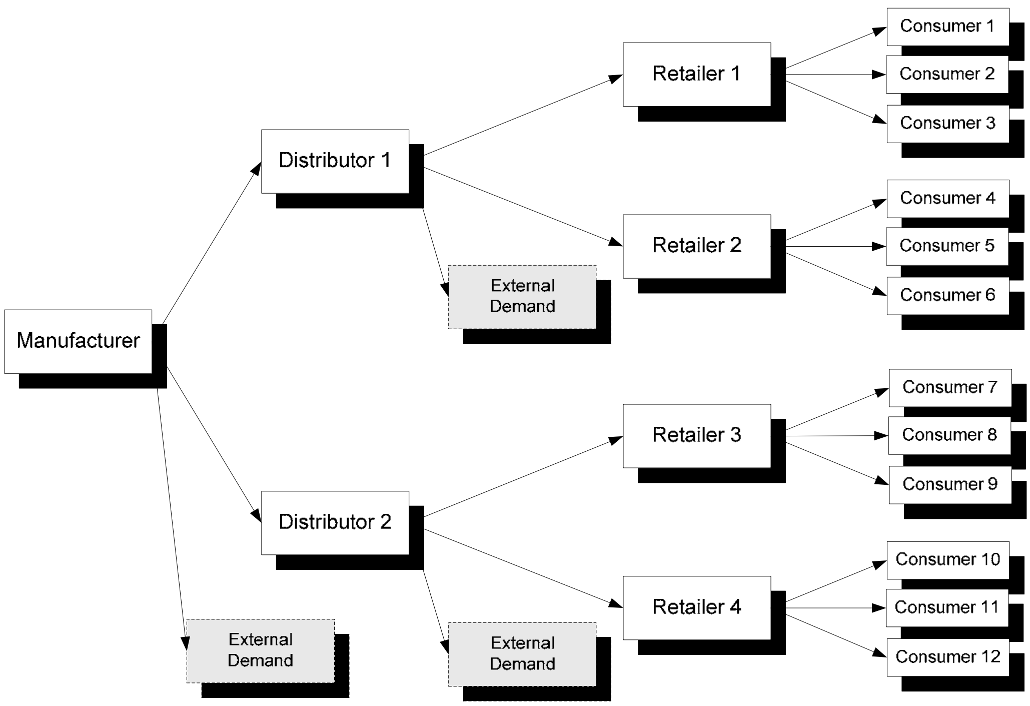

Figure 1: Supply Chain Structure.

Each supply chain member orders products from its supplier and sells them to its customers. In addition, the distributors and the manufacturer have external demand which is not part of the supply chain. The need for external demand comes from the fact that the order inter-arrival time for upstream companies increases. Without external demand, the manufacturer, for instance, would receive only a few orders per month from its distributors. As a consequence, he would estimate the demand during lead time based on strongly varying order data even if the demand is relatively constant. For a detailed analysis of this phenomenon see [Schm07]. Figure 1 illustrates the supply chain model under investigation.

2.1.2. Demand Structure

For each of the twelve consumers as well as for the external demand, a mean daily demand and a standard deviation may be defined. The demand is normally distributed and truncated at zero to ensure that only non-negative demand values are generated.

2.1.3. Order and Backorder Processing

Incoming orders are processed according to a first in first out rule. If the physical stock is equal to or higher than the quantity ordered, the demand is fulfilled completely. In out of stock situations suppliers deliver the available quantity and note backorders for the unfilled demand. As soon as inventory becomes available, all backorders are delivered before regular orders are processed.

2.1.4. Inventory Control

Inventory control is based on continuous review, where the inventory position is monitored on an hourly basis. It consists of the physical stock plus all products already ordered minus customer backorders. When products are shipped to customers, the inventory position decreases by the amount of products ordered. As soon as the inventory position falls below a critical reorder point (ROP), an order is placed immediately. Since the supplier needs time for processing the order and delivering the products, the shipment arrives after a fixed lead time. Figure 2 illustrates the implemented stochastic inventory policy.

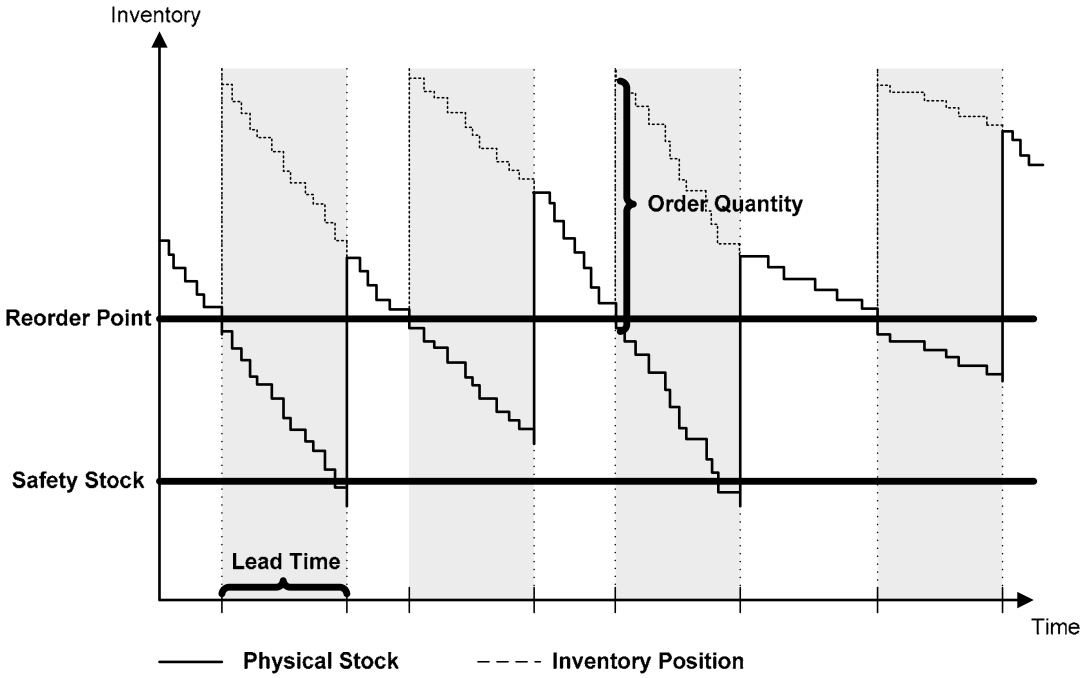

Figure 2: Stochastic Inventory Policy.

While both the order quantity and the lead time may be specified by the user of the simulation model, the reorder point is calculated dynamically by the simulation model based on the following formula [CaTe06; SiKS08]:

$$ROP = E(x) + z \cdot \sigma_x \,,$$

where $E(x)$ is the average demand during lead time and $z \cdot \sigma_x$ represents the safety stock which depends on the standard deviation of demand and a risk-attitude-specific safety factor *z*. Assuming that demand is normally distributed, this factor can be read from statistical tables to ensure that the probability of no stockouts during lead time is equal to a specified service level. For each stage a safety factor of z = 1.88 was chosen, which should lead to a service level of at least 97%.

The calculation of the average demand during lead time is based on monthly demand data. With the availability of new demand data every month, a new average lead time demand and a new standard deviation are calculated. As a result, the reorder point is not static and changes when new demand values become available.

2.2. Simulation Setup and Model Customization

The supply chain simulation model was built using the Extend simulation environment and is available upon request. The functionalities of the simulation model are described in the following subsections.

2.2.1. General Settings

After opening the simulation file, the model is automatically imported into the Extend simulation environment. A screenshot of the simulated supply chain is shown in Figure 3.

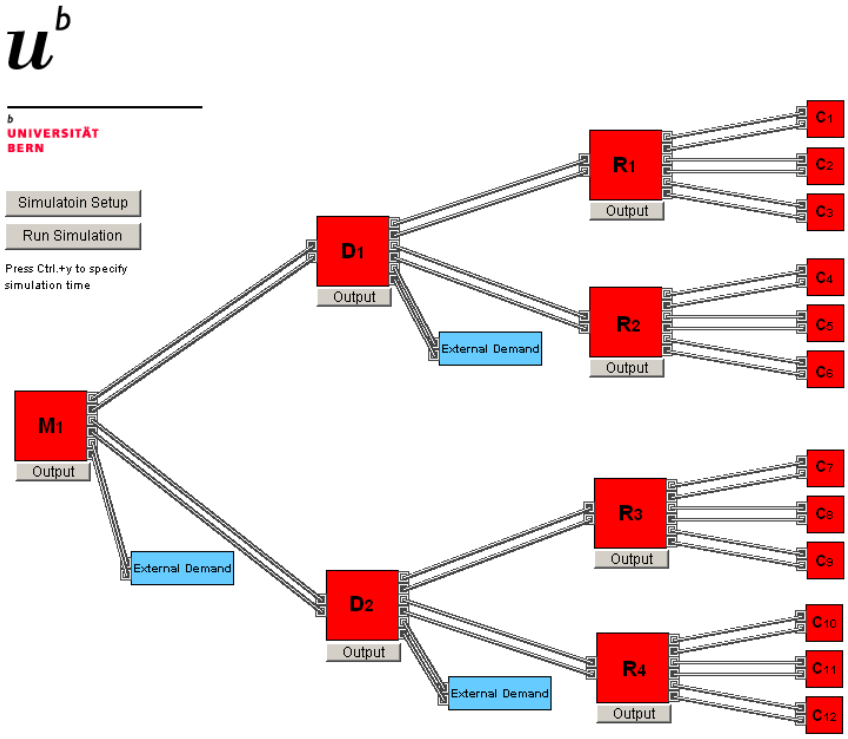

Figure 3: Supply Chain Simulation Model.

The simulation may be executed by clicking the button "Run Simulation". Using the default settings, the model runs for 1580 days. For the output analysis the first 500 days are deleted to account for warm-up effects. Thus, the time period under investigation is three years. The predefined simulation time may be changed by clicking Ctrl.+Y. In addition, the number of simulation runs may be set for multi-run simulations.

2.2.2. Parameter Specification

The model allows certain parameters to be modified. By clicking the button "Simulation Setup" the screen shown in Figure 4 appears.

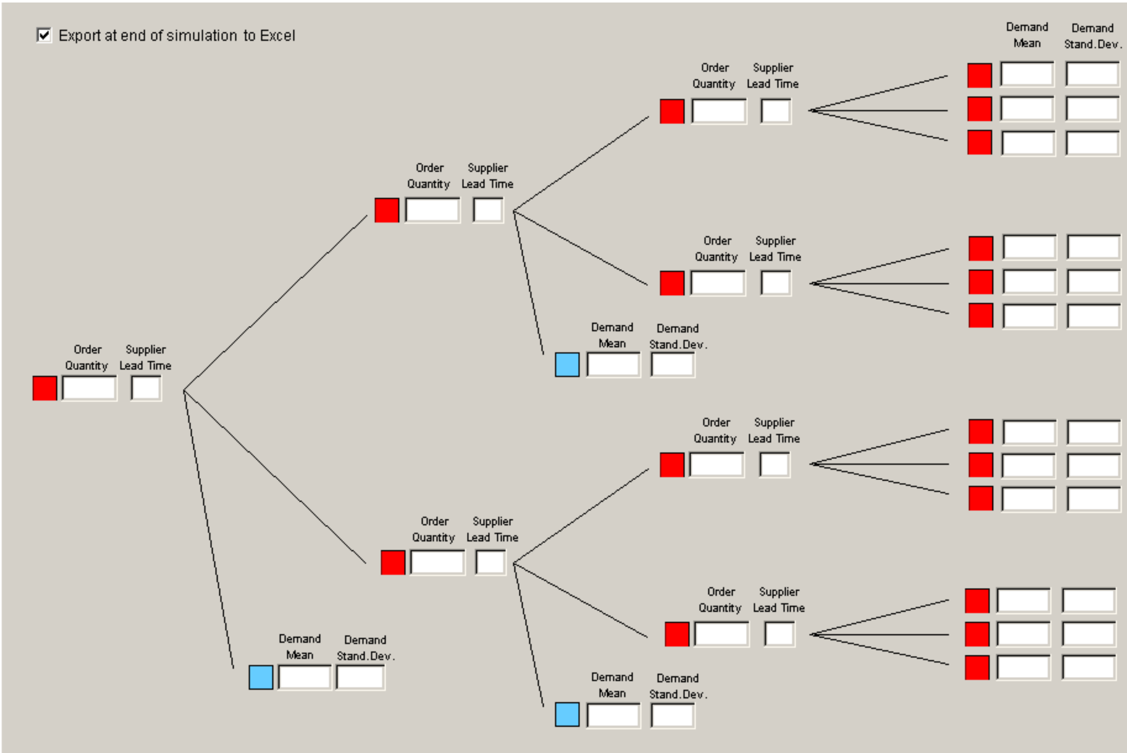

Figure 4: Simulation Setup.

For each supply chain member the order quantity and the supplier lead time may be specified. The normally distributed consumer demand as well as the external demand may be defined by setting a mean and standard deviation for the daily demand.

2.2.3. Advanced Model Development

Even though the parameter specification allows a comprehensive supply chain analysis, the model may be further developed with a basic knowledge of the Extend simulation environment. The modular composition of the model allows a rapid modification of basic model properties. For instance, the continuous review inventory policy may be replaced by a periodic review system for a subset of supply chain members.

To outline the interactions between model parameters and their effects on the supply chain performance, the model was intentionally designed with only a few stochastic processes. Of course, additional stochastic elements may be included. For instance, stochastic order quantities or stochastic lead times may be considered with marginal effort.

2.3. Simulation Output

For each supply chain member the output may be analyzed and visualized individually. By clicking the corresponding "Output" button in the simulation model, the screen shown in Figure 5 appears.

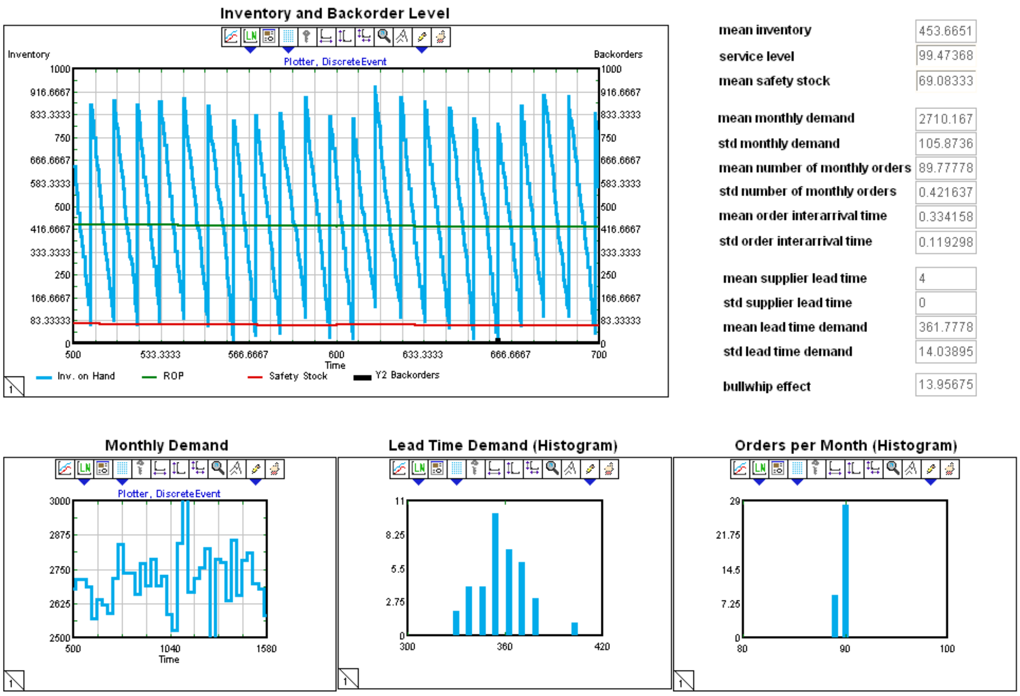

Figure 5: Simulation Output.

The output screen consists of graphs displaying demand, inventories, and backorders. Furthermore, certain output measures are computed automatically. A detailed description is presented in the following subsections.

2.3.1. Output Measures

To investigate the simulation results, the following output measures may be analyzed:

- Mean Inventory
- Mean Safety Stock
- Service Level measured by the proportion of orders that are completely fulfilled
- Mean and standard deviation of monthly demand
- Mean and standard deviation of incoming orders per month
- Mean and standard deviation of order inter-arrival time
- Mean and standard deviation of supplier lead time[1]
- Bullwhip effect.[2]

2.3.2. Graphical Output

The primary source for analyzing the output is the inventory and backorder level chart. It shows the physical stock, the backorder level, the reorder point, and the safety stock, (see Figure 6).

[1] Although the supplier lead time may be defined by the user, it is monitored since it may increase when suppliers can not deliver the products from stock.
[2] The bullwhip effect is calculated as the ratio of the variances of outgoing and incoming orders and indicates the percentage of demand variance amplification. For a detailed discussion of various measures of the bullwhip effect see [FrWo00].

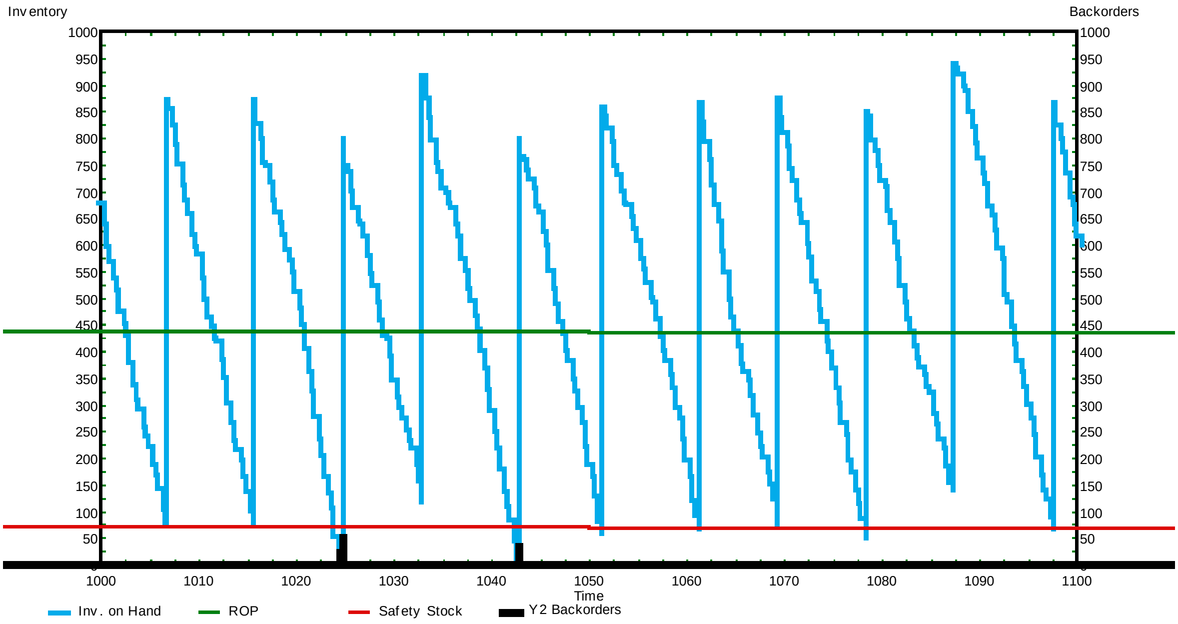

Figure 6: Inventory, Backorders, Reorder Point, and Safety Stock.

On the left vertical axis the units on stock are displayed, while the right vertical axis (Y2) shows the backorder quantity. The level of backorders is displayed by vertical black bars. For ease of comparison both axes, the inventory and the backorder quantity should have the same scale. The horizontal axis indicates the time horizon under investigation. All axes may be rescaled by double-clicking on the minimum or the maximum value. This may be helpful if one wishes to focus on a specific time interval. For instance, if backorders in a certain period are very high, one can take a closer look at this period to analyze possible reasons for this effect.

Incoming orders can be graphically monitored in three different ways (see Figure 7). First, the monthly demand values are displayed. Second, a histogram of the estimated lead time demand is shown and third, a histogram of the number of incoming orders per month is presented.

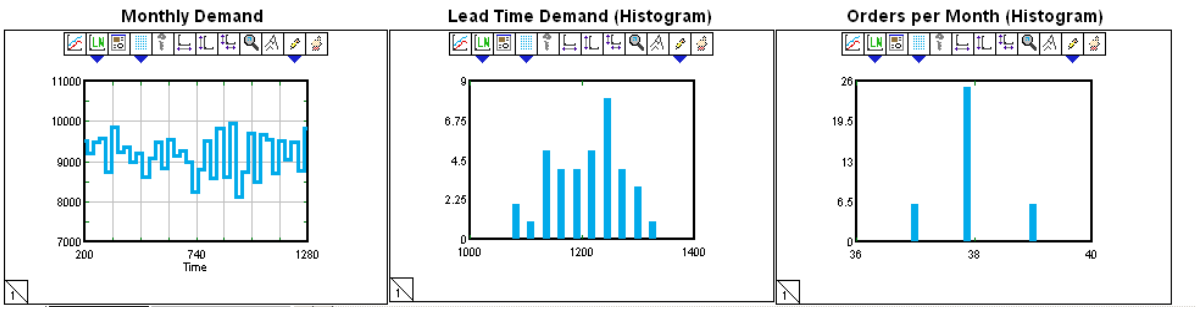

Figure 7: Monthly Demand, Lead Time Demand, and Number of Incoming Orders per Month.

2.3.3. Data Export

The simulation results can be exported into an Excel-file when the checkbox "Export at end of simulation" is activated. Export is supported for up to 10 simulation runs. The export file consists of an output for each simulation run to compare the results of one run between all supply chain members. For multiple simulation runs, the data are saved separately for each supply chain member. In addition, the mean output values for all supply chain members for multiple simulation runs are summarized in a separate sheet. Figure 8 shows the structure of the output sheet for the summarized data.

	M1	D1	D2	R1	R2	R3	R4
Mean Inventory							
Service Level							
Mean Safety Stock							
Mean Monthly Demand							
STD Monthly Demand							
Mean Number of Monthly Orders							
STD Number of Monthly Orders							
Mean Order Interarrival Time							
STD Order Interarrival Time							
Mean Supplier Lead Time							
STD Supplier Lead Time							
Mean Lead Time Demand							
STD Lead Time Demand							
Bullwhip Effect							

Figure 8: Simulation Output in Excel (Summary).

3 DEVELOPMENT OF A BASE MODEL

In this section the supply chain simulation model described in the previous section is parameterized. The lead times, the demand settings as well as the order quantities placed by each member of the supply chain are specified. To ensure the correctness of the simulation model, an intensive verification procedure is performed.

3.1. Specification of Lead Times

In the real world, lead times are strongly dependent on the industry in which a company operates. Since lead times may not be specified universally, several authors assume identical lead times for each company [cf. Ster92; MPLV02; Chen98; CRGE98; CKHH04]. According to [CKHH04], we also assume lead times of four days for each company except the consumers. It is assumed that consumers go directly to the retail outlet and buy the products immediately. Of course, the lead times may be modified by the user of the simulation model.

3.2. Specification of Demand

Every retailer receives the demand of three consumers. The consumers of a given retailer are modeled identically but differ between retailers. To ensure that the demand is normally distributed, the standard deviation is set lower than 1/3 of the mean daily demand. With these settings, the probability of positive demand is at least 99%. Figure 9 shows the demand settings in the base model.

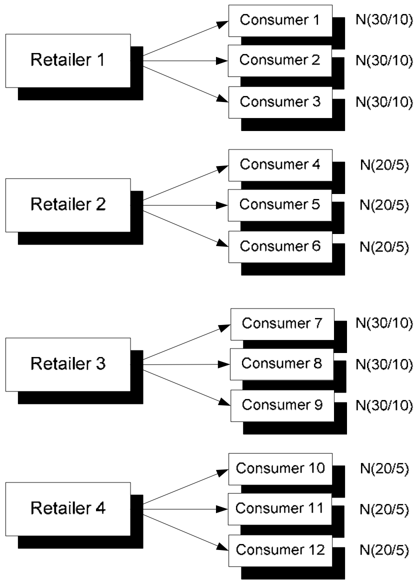

Figure 9: Demand Settings in the Base Model.

The normally distributed external demand is set equal to the summed daily echelon demand. For instance, the external daily demand of the distributors is set to 150 units since the daily demand of the distributors is 3*30+3*20=150. The external demand of the manufacturer is set to 600 since the sum of the mean daily demand of both distributors is 600. The standard deviation of the external demand is set to 1/3 of the respective mean to ensure that the probability of positive demand is at least 99%.

3.3. Specification of Order Quantities

In reality, companies determine their order quantities based on a variety of decision criteria. The order quantity may depend on the cost of storing the products, the ordering costs or synergies in transportation by combining several orders in one transportation order.

Since costs of the activities are not considered in this simulation model, the order quantities may be specified directly by the simulation user. However, several conditions have to be satisfied to determine adequate order quantities. First, the order quantity should be higher for upstream than for downstream companies. Because upstream companies receive orders from different channels, they have a higher demand. Second, the order quantity has to be set higher than the reorder point. This condition ensures that the physical inventory is higher than the reorder point whenever a shipment arrives. If the order quantity is lower, a new order would be placed before the products already ordered actually arrive. To avoid this rather unrealistic situation, the order quantities are set considerably higher than the allowed minimum. For retailers 1 and 3 an order quantity of 800 and for retailers 2 and 4 an order quantity or 400 units is chosen. Both distributors order 7000 units and the manufacturer 50000 units when placing an order. A summary of all parameter settings is presented in Figure 10.

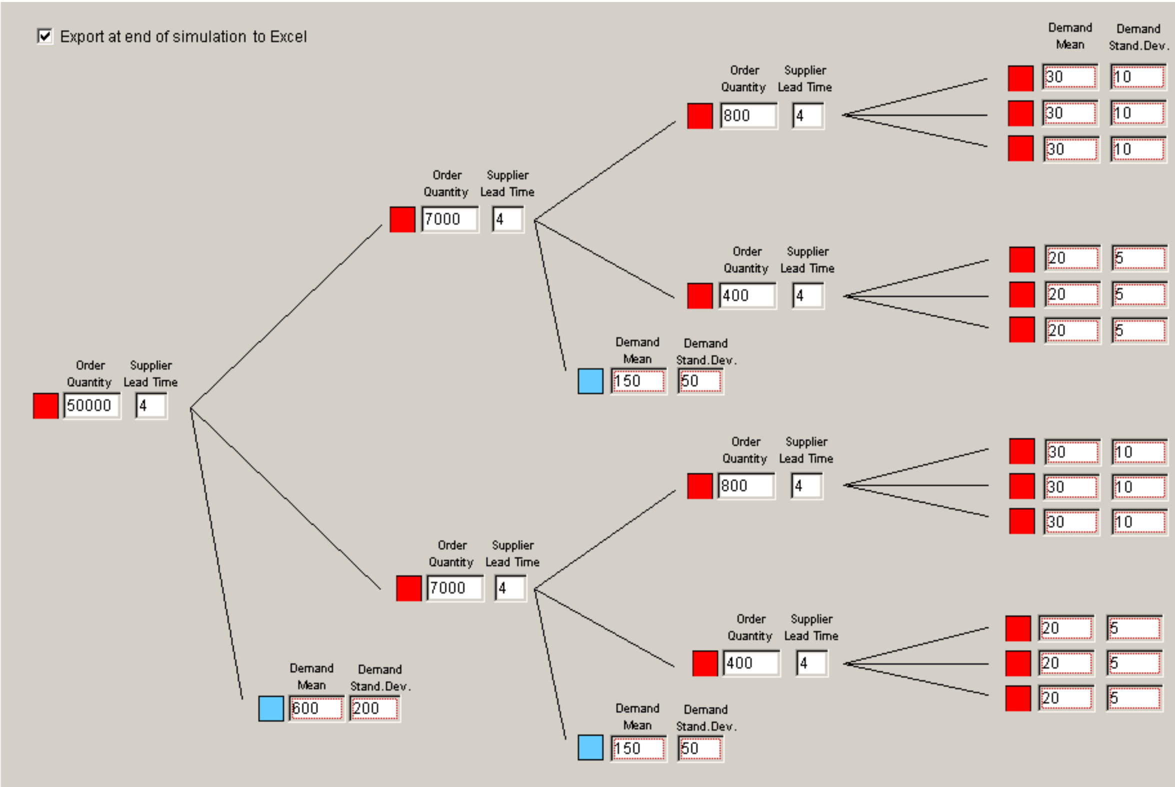

Figure 10: Summary of Simulation Settings in the Base Model.

3.4. Verification, Validation, and Testing

One of the most challenging tasks in developing a simulation model is to provide evidence that the model works as intended. The correctness of a model may be analyzed in two ways. First, one has to examine whether the conceptual model has been translated correctly into a computer program (verification) and second, whether the model is an accurate representation of the real system under investigation (validation) [LaKe00; BCNN05]. Thus, verification and validation addresses two questions [Balc03]:

1. Are we creating the simulation model right (verification)?
2. Are we creating the right simulation model (validation)?

However, in practical applications, the distinction between these two terms is often not so well defined [Balc98]. The scientific literature proposes many verification and validation techniques [cf. Klei95; Balc98; LaKe00; Sarg04; BCNN05]. In the following sections, all supply chain members are tested for a correct implementation focusing on three aspects:

- Test of the supply chain member without stochastic elements
- Test of demand distribution in case of stochastic demand
- Test of reorder point calculations.

3.4.1. Consumers

To test whether the simulated data are normally distributed, a Kolmogorov-Smirnov test was performed based on a simulation run of 5000 days. Table 1 shows the statistical output for the consumers and for the external demand. An asymptotical significance smaller than 0.05 would indicate that the data differ significantly from a normal distribution on a level of significance of 5%. The statistical tests show that there are no significant differences from a normal distribution for all 12 consumers and the external demand.

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12
Mean	30.08	30.02	29.96	20.06	20.02	19.97	29.80	30.13	30.07	19.90	19.94	20.12
STD	10.07	9.96	10.02	4.89	4.94	4.99	10.17	9.97	9.93	4.99	5.00	5.00
K-S	0.71	0.59	0.53	0.50	0.48	0.70	0.75	0.51	0.84	0.64	0.49	1.15
Sig.	*0.70*	*0.88*	*0.94*	*0.97*	*0.97*	*0.71*	*0.62*	*0.96*	*0.48*	*0.81*	*0.97*	*0.14*

	ExtD1	ExtD2	ExtM
Mean	149.88	150.53	597.84
STD	49.57	50.17	201.32
K-S	0.53	0.62	0.83
Sig.	*0.94*	*0.83*	*0.50*

STD=Standard Deviation; K-S = Kolmogorov-Smirnov Test Statistic; Sig. = Asymptotical Significance (2-sided)

Table 1: Kolmogorov-Smirnov Test for Normal Distribution (N=5000).

3.4.2. Retailers

To test whether the retailers are correctly implemented, the simulation was run without variability in consumer demand. This should lead to a service level of 100% for all retailers due to deterministic demand. The reorder point should be equal to the average demand during lead time with a safety stock of zero. Table 2 shows the simulation output for 10 simulation runs of 1580 days each.

	Retailer 1	Retailer 2	Retailer 3	Reteiler 4
Run 1	97.53	100.00	97.53	100.00
Run 2	97.53	100.00	97.53	100.00
Run 3	97.53	100.00	97.53	100.00
Run 4	97.53	100.00	97.53	100.00
Run 5	97.53	100.00	97.53	100.00
Run 6	97.53	100.00	97.53	100.00
Run 7	97.53	100.00	97.53	100.00
Run 8	97.53	100.00	97.53	100.00
Run 9	97.53	100.00	97.53	100.00
Run 10	97.53	100.00	97.53	100.00
Average	**97.53**	**100.00**	**97.53**	**100.00**

Table 2: Service Levels under Deterministic Demand.

Obviously, the service levels of retailers 1 and 3 are considerably lower than 100%, whereas the service levels of retailer 2 and 4 are as expected. The reason for this rather confusing phenomenon lies in the interaction of consumer demand with order quantity. Since the demand is deterministic, a shipment should arrive exactly at the moment when no physical inventory is available. However, this condition only holds when the reorder point is hit exactly. With an order quantity of 400 and a demand of 20, the reorder point of 3*20*4=240 for retailers 2 and 4 is hit exactly after 8 deliveries. Figure 11 shows the resulting graph for the inventory position of retailer 2 in a time frame of 40 days.

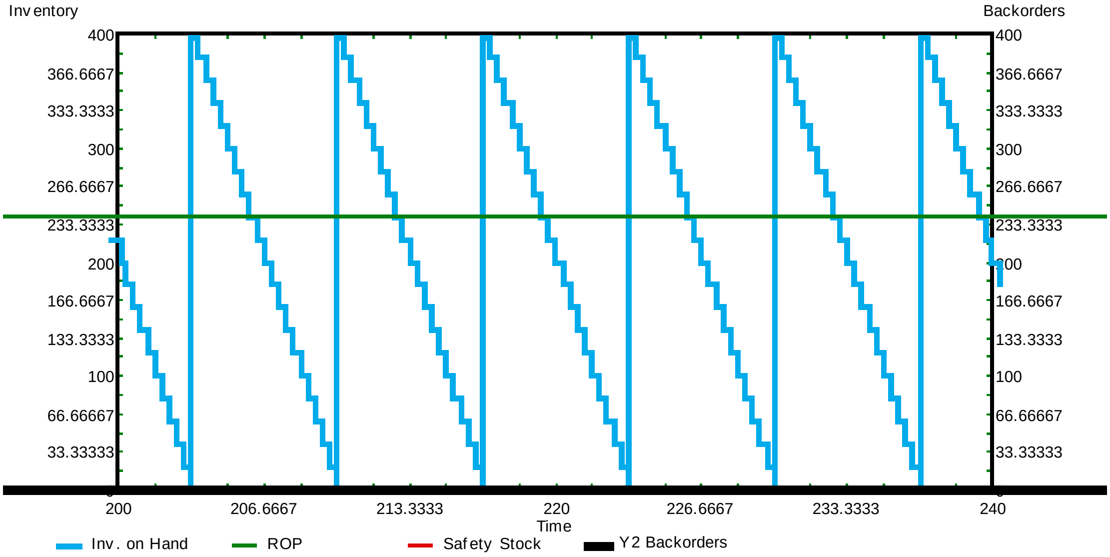

Figure 11: Inventory Position and Reorder Point under Deterministic Demand (Retailer 2).

With an order quantity of 800 and a demand of 30 the reorder point of 3*30*4=360 for retailer 1 and 2 is not hit exactly. A new order is placed after 15 deliveries. At this point, the inventory position is 800-450=350 and thus lower than the reorder point. Hence, the physical inventory is too low to fulfill demand during lead time. Figure 12 illustrates the phenomenon for retailer 1.

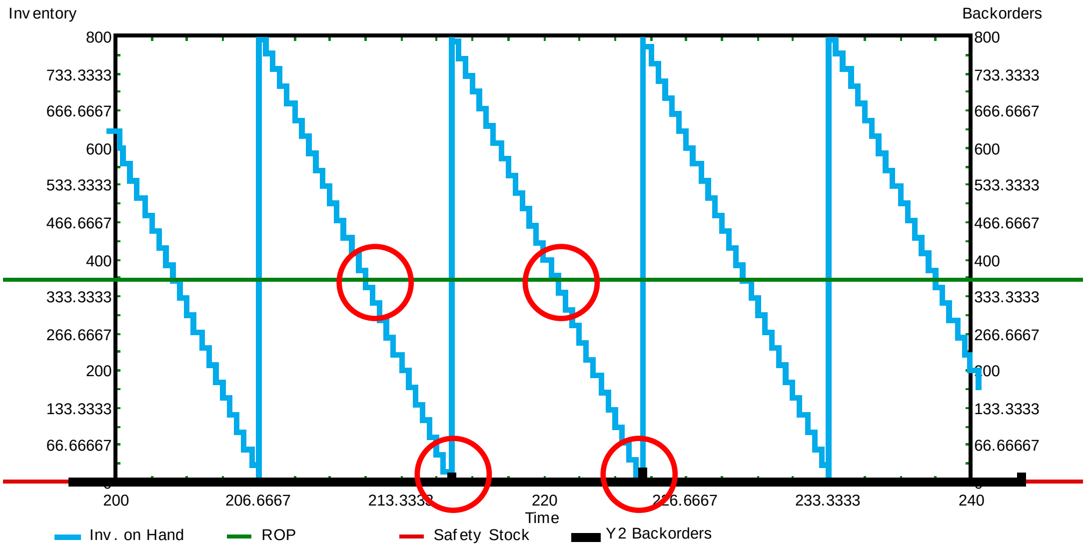

Figure 12: Inventory Position and Reorder Point under Deterministic Demand (Retailer 1).

In general, the reorder point is only hit exactly if the following condition holds:

$$\frac{Order\ Quantity}{Initial\ Mean\ Daily\ Demand} = integer$$

Otherwise, backorders may occur even if the demand is deterministic.

To test the correctness of the retailer implementation under stochastic demand, a test for normally distributed demand was performed for the four retailers. Since the estimation of lead time demand by the retailers is based on monthly data, the distributions of these data (and not of daily demand) were tested. Demand data for 5000 days were collected, resulting in 165 data elements for each retailer. Table 3 indicates that the monthly demand data from all retailers do not significantly differ from a normal distribution (asymptotical significance > 0.05).

	r1	r2	r3	r4
Mean	2758.85	1844.30	2745.95	1841.70
STD	97.72	51.54	95.93	47.47
K-S	0.56	0.75	0.66	0.86
Sig.	0.91	0.63	0.78	0.45
STD=Standard Deviation; K-S = Kolmogorov-Smirnov Test Statistic; Sig. = Asymptotical Significance (2-sided)				

Table 3: Test for Normal Distribution for Retailer's Monthly Demand Data (N=165).

Moreover, the retailers mean demand and standard deviation should equal the sum of each normally distributed consumer demand. Since the retailer monitors the monthly demand data, the daily demand data should be multiplied by 30. For retailers with a demand of N(30/10) for each consumer, the monthly demand mean should equal

$$30 \cdot \sum_{1}^{i} \mu_{c_i} = 30 \cdot (30 + 30 + 30) = 2700$$

where μ_{c_i} represents the mean demand from consumer *i*. The standard deviation may be calculated as

$$\sqrt{30 \cdot \sum_{1}^{i} \sigma^2{}_{c_i}} = \sqrt{30 \cdot (10^2 + 10^2 + 10^2)} = \sqrt{30} \cdot \sqrt{3} \cdot 10 = 94.87$$

Similarly, the monthly demand distribution for N(20/10) should have a mean of

$$30 \cdot \sum_{1}^{i} \mu_{c_i} = 30 * (20 + 20 + 20) = 1800$$

with a standard deviation of

$$\sqrt{30 \cdot \sum_{1}^{i} \sigma^2{}_{ci}} = \sqrt{30 \cdot (5^2 + 5^2 + 5^2)} = 47.43$$

Analyzing the experimental data shown in Table 3, it is obvious that the mean and standard deviation are very close to the exact values. The slight deviations may result from the fact that the consumer demand is rounded up to the next integer.

To check whether the reorder point calculations are implemented properly, the model output is compared with results of mathematical computations. The reorder points for retailers 1 and 3 should equal

$$ROP = E(x) + z \cdot \sigma_x = 2700 \cdot \frac{4}{30} + 1.88 \cdot 94.87 \cdot \sqrt{\frac{4}{30}} = 425.13$$

and for retailers 3 and 4

$$ROP = 1800 \cdot \frac{4}{30} + 1.88 \cdot 47.43 \cdot \sqrt{\frac{4}{30}} = 272.56$$

When comparing the results of these computations with the data obtained from the simulation model, no significant differences are observed. The reorder points of retailers 1 and 3 are around 430, whereas the reorder points of retailers 2 and 4 are close to 280. The slightly higher reorder points obtained from the simulation model may be explained by the rounding of the demand data which leads to a higher average demand during lead time.

3.4.3. Distributors

Tests similar to those for the retailers were also performed for the distributors. First, the distributors are tested without variability in demand. Second, the demand distribution is tested for stochastic demand and third, the correctness of the reorder point calculations is examined. To test the correct implementation of the distributors, all retailers are omitted from the model and demand is only generated by the external demand. The daily demand is set to 150 units for deterministic demand and to N(150,50) for stochastic demand.

For deterministic demand, the service level for both distributors should equal 100%. Since the ratio of order quantity and average daily demand is not an integer value (7000/150=46.6), the service levels are lower than 100% due to the fact that the reorder point is not hit exactly. Figure 13 shows an extract of the inventory position curve.

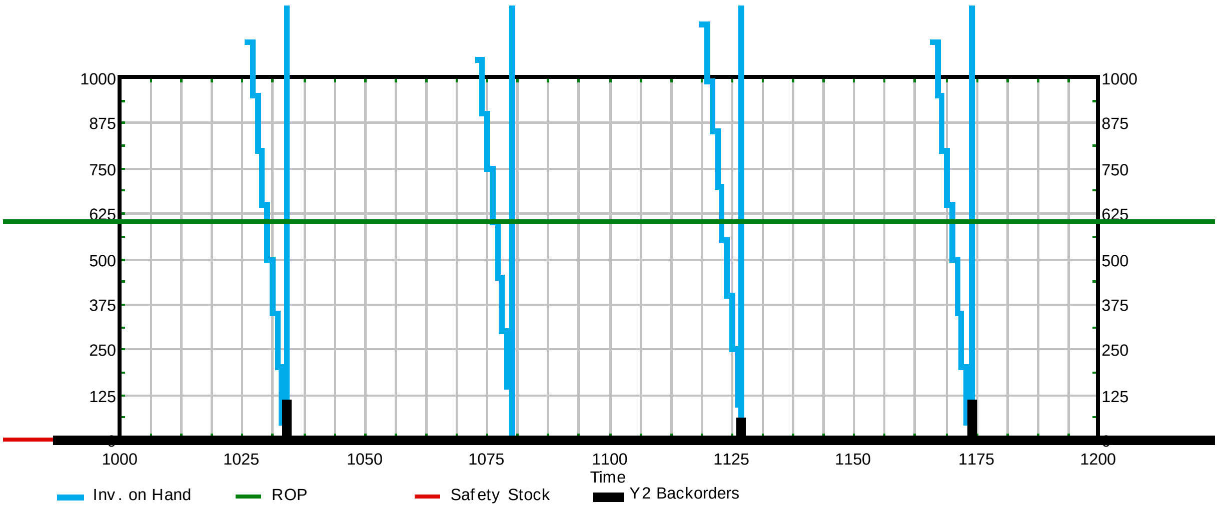

Figure 13: Inventory Position and Reorder Point under Deterministic Demand (Distributor 1).

To test the demand distribution for normality in case of stochastic demand, the simulation was run for 5000 days, producing a data set of 165 monthly demand values. The asymptotical significance of the Kolmogorov-Smirnov test of 0.94 for distributor 1 and 0.92 for distributor 2 indicates that the data is normally distributed (at a level of significance of 5%).

The reorder points of both distributors are around 800 units. This is marginally higher than the expected reorder point of

$$ROP = 150 \cdot 4 + 1.88 \cdot 50 \cdot \sqrt{4} = 788$$

Again, the difference may be due to a rounding of demand data leading to a higher demand during lead time.

3.4.4. Manufacturer

Findings similar to those for the retailers and the distributors are also obtained for the manufacturer. Again, because the ratio of order quantity and daily demand is not an integer value for the manufacturer, the service level under deterministic demand is lower than the expected 100%. With an asymptotical significance of 0.57, the monthly demand data are normally distributed on a significance level of 5%. The reorder point of 3190 is again a bit higher than the expected value of 3152.

4 SIMULATION RESULTS OF THE BASE MODEL

The previous section described the development of the base model. In this section, the simulation output of this base model is discussed in detail. The output analysis was performed in two ways. First, for one member of each stage, graphical outputs of inventories, backorders, and incoming orders are presented. Second, a multi-run simulation of the base model was performed. The model was executed for 100 simulation runs, where one run consists of 1580 days. To account for warm-up effects, the first 500 days were deleted from the statistical analysis.

4.1. Results for the Retailers

The primary source for analyzing the output is the inventory and backorder chart. Figure 14 shows this chart for retailer 1 for a time period of 60 days.

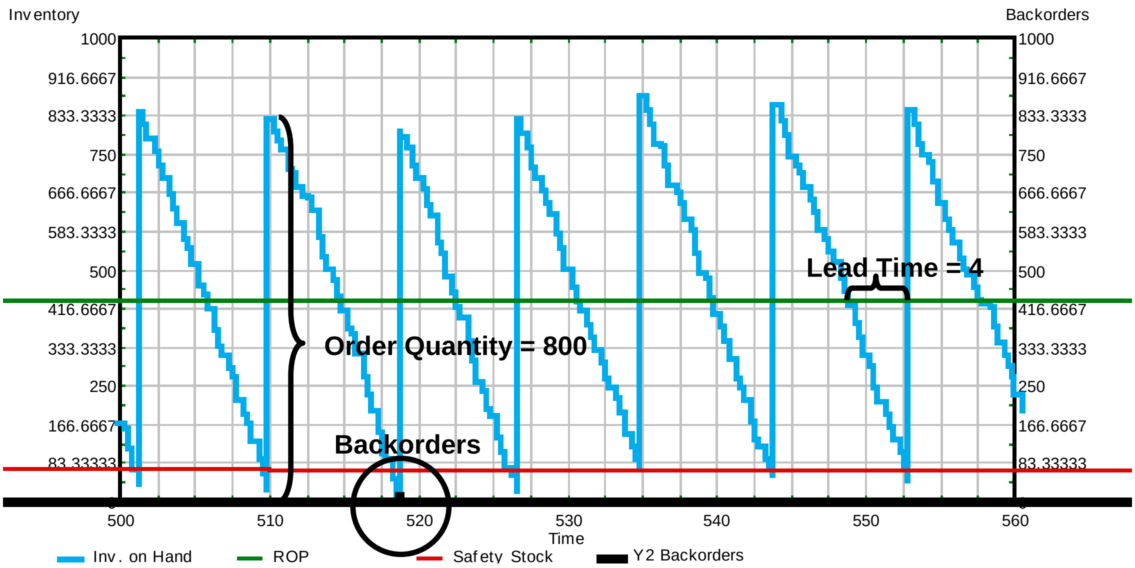

Figure 14: Inventory and Backorder Chart (Retailer 1).

Due to the relatively stable demand, the inventory decreases continuously over time and results in a stable reorder point and safety stock. The reorder point is around 430 and the amount of safety stock is 70. As soon as the inventory is lower than the reorder point, an order is placed for 800 units. The products are shipped after a lead time of four days. When the demand during lead time is higher than expected, backorders are shown in the chart with black bars (e.g. before day 520). Of course, all axes may be rescaled by modifying the minimum or maximum value.

Other sources for analyzing the model output are the charts of the demand per month and the distribution of the lead time demand. Figure 15 shows both graphs for retailer 1. The chart on the left depicts that the demand has a range of approximately 2500 to 3000 units per month. The histogram of the lead time demand presented in the histogram on the right is close to a normal distribution with a mean of around 360 units and a standard deviation of 15.

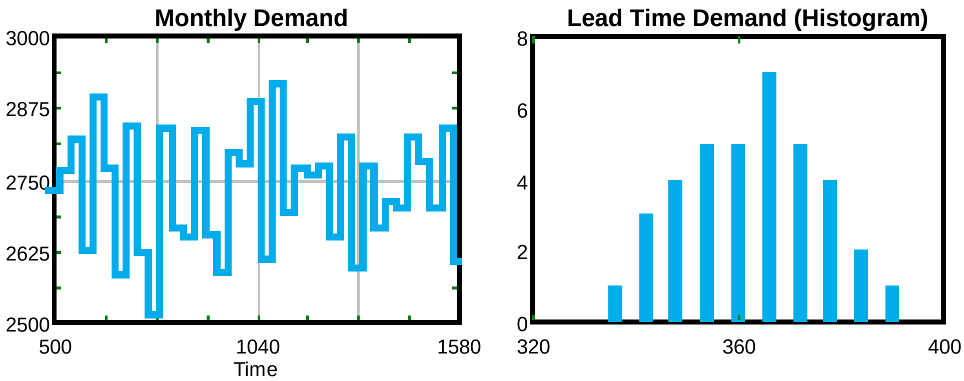

Figure 15: Monthly Demand and Distribution of Lead Time Demand (Retailer 1).

For all retailers, the output of the multi-run simulation is presented in Table 4. It shows that retailers 1 and 3 do not differ significantly from each other. A supplementary ANOVA supports this finding. This gives confidence in the simulation model since retailers 1 and 3 have the same consumer demand structure. The same holds for retailers 2 and 4. Since the retailers 1 and 3 as well as retailers 2 and 4 do not significantly differ from each other, the differences in the output are only discussed for retailer 1 and 2.

	R1	R2	R3	R4
Mean Inventory	452.74	225.30	451.48	225.33
Service Level	99.60	99.45	99.50	99.48
Mean Safety Stock	65.70	33.83	65.02	33.58
Mean Monthly Demand	2744.84	1846.66	2744.62	1844.40
STD Monthly Demand	94.36	47.53	93.91	46.19
Mean Number of Monthly Orders	89.88	90.00	89.88	90.00
STD Number of Monthly Orders	0.34	0.01	0.34	0.02
Mean Order Interarrival Time	0.33	0.33	0.33	0.33
STD Order Interarrival Time	0.12	0.12	0.12	0.12
Mean Supplier Lead Time	4.02	4.01	4.01	4.01
STD Supplier Lead Time	0.11	0.09	0.10	0.08
Mean Lead Time Demand	366.44	246.69	366.41	246.38
STD Lead Time Demand	12.58	6.34	12.53	6.16
Bullwhip Effect	18.78	18.14	19.08	18.85

Table 4: Simulation Results for the Retailers in the Base Model.

Due to the higher order quantity placed by retailer 1 the mean inventory is higher than that of retailer 2. The demand distribution mainly influences the mean and standard deviation of monthly demand (or lead time demand) and, thus, the amount of the safety stocks. Due to the higher mean and standard deviation of the consumer demand, retailer 1 needs a higher amount of safety stock to achieve the desired service level.

The service levels of all retailers are higher than 99%. They differ from the expected 97% because the service level is measured as the ratio of completely fulfilled orders and not (as in the derivation of the reorder point calculation) as the probability of stockouts during lead time.

Retailer 2 receives 90 orders per month, whereas the mean number of monthly orders of retailer 1 is slightly lower. The lower value may be explained by the fact that it is more probable that consumers have an order quantity of zero in case of a distribution of N(30,10) than in case of N(20,5). However, the small standard deviation of the monthly orders also for retailer 2 indicates that in rare cases a consumer has an order quantity of zero. Since each retailer receives the daily demand of three consumers, the mean order inter-arrival time is 0.33. The mean supplier lead time is not exactly 4 days as defined in the simulation setup because the suppliers may run into a stockout situation where they can not deliver the products in time.

For all retailers the bullwhip effect is around 18, which indicates that the variance of the outgoing orders per month is 18 times higher than the variance of monthly demand. This surprisingly high value is the result of the infrequent orders placed by the retailers. Figure 16 shows the histogram of the outgoing order quantities compared to the histogram of incoming demand of retailer 1 for one simulation run.

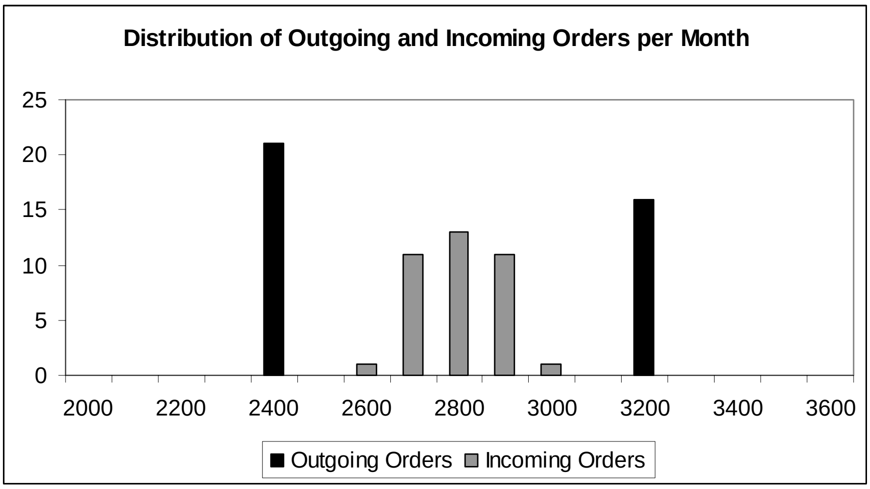

Figure 16: Distribution of Outgoing and Incoming Orders (Retailer 1).

Retailer 1 places either 3 or 4 orders per month leading to a monthly outgoing order quantity of 2400 or 3200 units per month. Although the mean order quantities are identical for incoming and outgoing orders, the variance of the outgoing orders is significantly higher resulting in a high bullwhip effect.

4.2. Results for the Distributors

The output graphs of the distributors differ significantly from those of the retailers. Figure 17 shows the inventory and backorder chart for distributor 1. It is obvious that the inventory no longer decreases linearly but drops down at certain points. The rapid inventory decrease comes from the high order quantities placed by the retailers. For instance, on day 514, retailer 1 places an order for 800 units or on day 516 retailer 2 places an order for 400 units.

Figure 17: Inventory and Backorder Chart (Distributor 1).

Looking at the demand charts, it is obvious that the distributors have a higher monthly demand than the retailers. The mean monthly demand for both distributors is close to 9000 units. Figure 18 shows that the scarce orders placed by the retailers may lead to an unexpected distribution of the lead time demand.

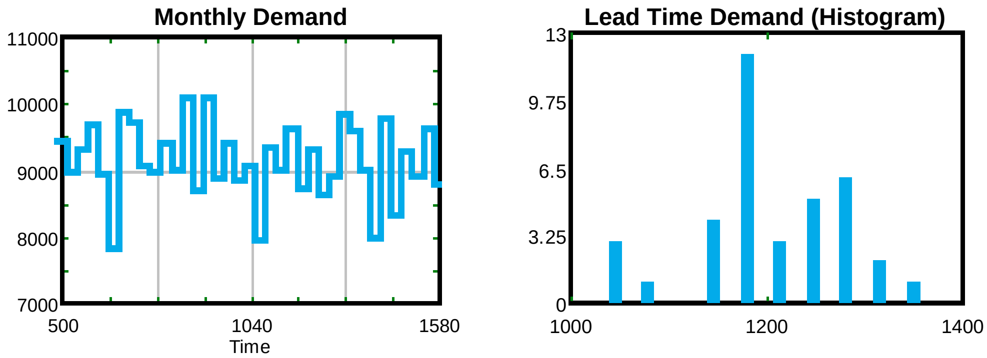

Figure 18: Monthly Demand and Distribution of Lead Time Demand (Distributor 1).

The results of the multi-run simulation for both distributors are summarized in Table 5. As expected, the results for distributor 1 do not differ significantly from those of distributor 2. The mean inventory is nearly half of the order quantity of 7000. The service levels are again higher than the expected 97%. The safety stock needed to maintain the service level is around 380 units.

	D1	D2
Mean Inventory	3875.23	3890.71
Service Level	98.35	98.44
Mean Safety Stock	379.40	383.50
Mean Monthly Demand	9110.47	9095.60
STD Monthly Demand	515.66	523.99
Mean Number of Monthly Orders	38.00	38.00
STD Number of Monthly Orders	0.72	0.74
Mean Order Interarrival Time	0.79	0.79
STD Order Interarrival Time	0.29	0.29
Mean Supplier Lead Time	4.09	4.07
STD Supplier Lead Time	0.39	0.31
Mean Lead Time Demand	1215.21	1213.21
STD Lead Time Demand	68.75	69.87
Bullwhip Effect	41.59	40.32

Table 5: Simulation Results for the Distributors in the Base Model.

Since the distributors have additional external demand, the mean monthly demand consists of the mean supply chain demand of 30*(3*30+3*20) = 4500 and the external demand of 30*150 = 4500. Due to rounding of the data, the effective mean monthly demand is slightly higher than expected. The bullwhip effect of 40 indicates that the variance of outgoing orders per month is 40 times higher than the variance of the monthly incoming demand. Due to the low order frequency and the high order quantities per order, the variance of outgoing orders is higher than the variance of incoming order quantities. Figure 19 shows the histogram of outgoing and incoming order quantities per month. The distributor places only one or two orders per month leading to a monthly outgoing order quantity of either 7000 or 14000 units. Obviously, the variance of outgoing orders is massively higher than the variance of incoming orders, resulting in a high bullwhip effect.

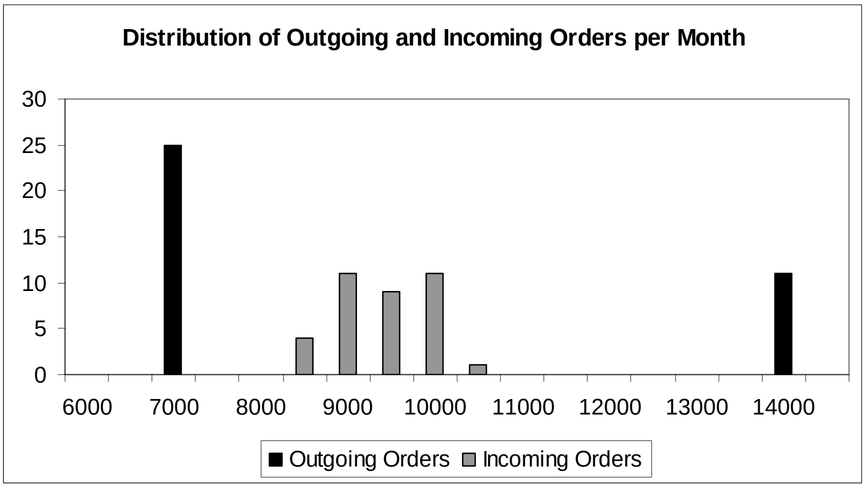

Figure 19: Distribution of Outgoing and Incoming Orders (Distributor 1).

4.3. Results for the Manufacturer

The effects discussed for the distributors in the previous section are even more marked for the manufacturer. The inventory chart in Figure 20 illustrates the rapid decrease in inventory when a distributor places an order for 7000 units.

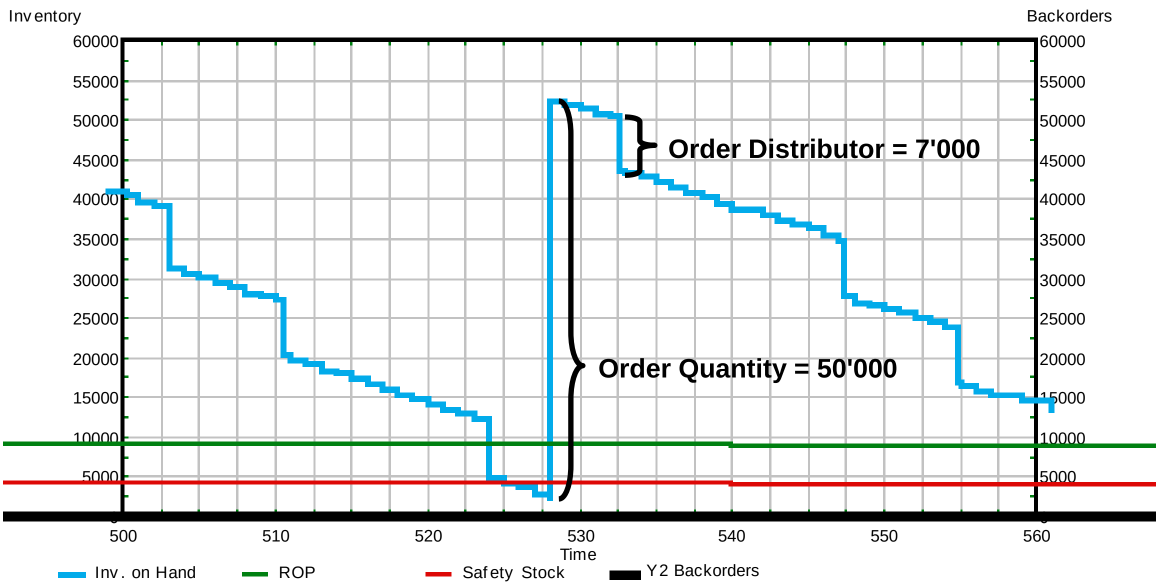

Figure 20: Inventory and Backorder Chart (Manufacturer).

Figure 21 shows the demand per month and the lead time demand distribution for the manufacturer. It is obvious that the resulting distribution of lead time demand differs significantly from a normal distribution.

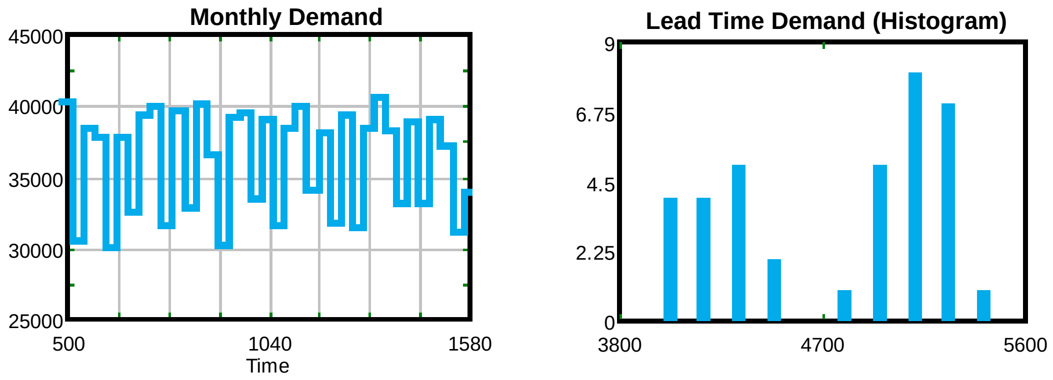

Figure 21: Monthly Demand and Distribution of Lead Time Demand (Manufacturer).

The results for the manufacturer are summarized in Table 6. The higher order quantity placed by the manufacturer leads to a high mean inventory of almost 29000 units. To provide the predefined service level, a relatively high safety stock of 3627 units is necessary. Since no capacity constraints are assumed in production, the supplier lead time is exactly 4 days with a standard deviation of 0.

	M1
Mean Inventory	28752.23
Service Level	98.22
Mean Safety Stock	3627.16
Mean Monthly Demand	36255.12
STD Monthly Demand	4931.06
Mean Number of Monthly Orders	32.57
STD Number of Monthly Orders	0.71
Mean Order Interarrival Time	0.92
STD Order Interarrival Time	0.24
Mean Supplier Lead Time	4.00
STD Supplier Lead Time	0.00
Mean Lead Time Demand	4834.49
STD Lead Time Demand	657.47
Bullwhip Effect	22.89

Table 6: Simulation Results for the Manufacturer in the Base Model.

As a result of the high order quantities placed by the distributors, the standard deviation of monthly demand is extremely high (approximately 1/8 of the mean monthly demand). Interestingly, the bullwhip effect of around 23 is lower than for the distributors. This effect results from the high incoming order quantities placed by the distributors which are leading to a higher variance of incoming orders. The higher variability results in a smaller bullwhip effect.

5 EXPERIMENTS AND DISCUSSION OF RESULTS

To analyze the impact of lead time, variability of demand, and order quantity, three experiments are conducted. The results of each experiment are compared with the results obtained from the base model. For each experiment, a multi-run simulation of 10 runs was performed. As in the base model, one run consists of 1580 days with the first 500 days deleted to account for warm-up effects. Since the parameters contain certain interdependencies, a modification of the inputs is restricted to specific ranges. For instance, the lead time may not be increased arbitrarily since at a specific level, the fixed order quantity would be lower than the reorder point. Thus the inventory would not suffice to meet the demand during lead time and would result in higher back-orders.

5.1. Modification of Lead Times

In the first experiment, the lead time values of retailers 1 and 2 were reduced from initially 4 days to 3, 2, and 1. Since the lead times directly affect the level of the safety stocks, we expect a decrease in lead times to result in a reduction of safety stocks for the retailers. As a consequence, the mean inventory too should decrease. For all other output measures, no significant effects are expected. Figure 22 shows the results for retailer 1, by way of example. The bars show the changes in percent compared to the base model. As expected, a reduction of the lead time may lead to lower safety stocks and thus to lower mean inventories. Reducing the lead time from 4 days to 1 would result in a reduction of the safety stock of around 50% and an inventory reduction of 7%. All other output measures are only marginally affected.

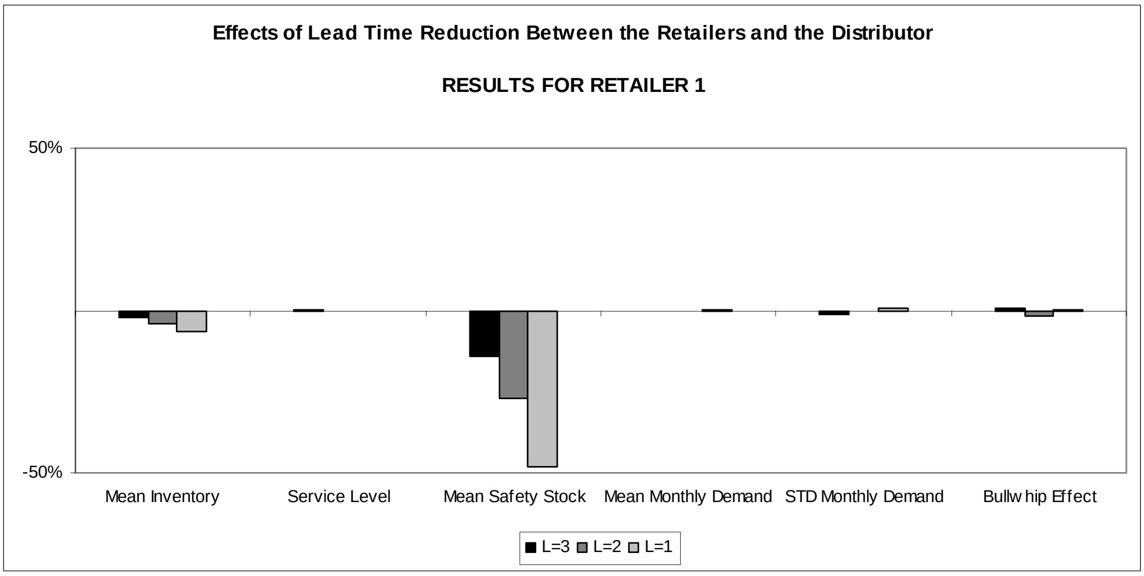

Figure 22: Impact of Lower Lead Times for Retailer 1.

The reduction of the lead time between the retailers and the distributor has no significant effects for the distributor. Figure 23 shows the results for distributor 1. The small variability of the output measures may be explained by the fact that the standard deviation of the demand may vary slightly even if the consumer demand has the same mean and standard deviation. Hence, the safety stocks and the bullwhip effect may also vary slightly.

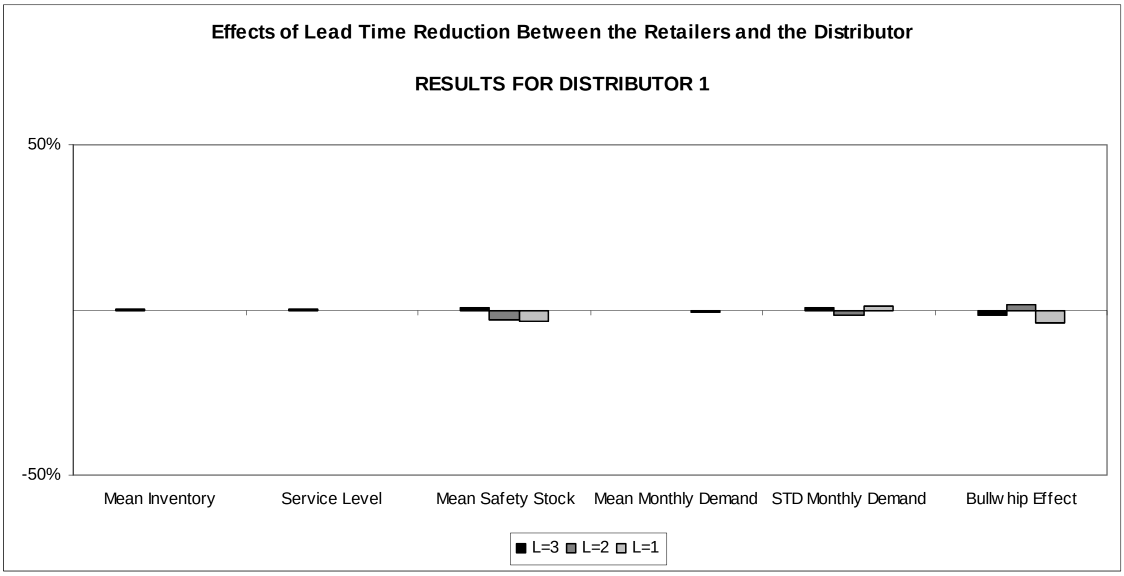

Figure 23: Impact of Lower Lead Times for Distributor 1.

5.2. Modification of Demand Variability

To test the impact of changes in the variability of demand, the initial consumer demand distribution of N(30,10) and N(20,5) was increased for consumer 1 to 6. Table 7 shows the three scenarios considered.

	Moderate Variability	Medium Variability	High Variability
Consumers 1-3	N(30,15)	N(30,30)	N(30,60)
Consumers 4-6	N(20,10)	N(20,20)	N(20,40)

Table 7: Example of Monthly Demand Data.

To provide an almost identical service level, a higher safety stock is required when uncertainty of future demand is higher. Increasing demand variability should therefore lead to higher safety stocks and thus to higher mean inventories for the retailers. Figure 24 shows the results for retailer 1.

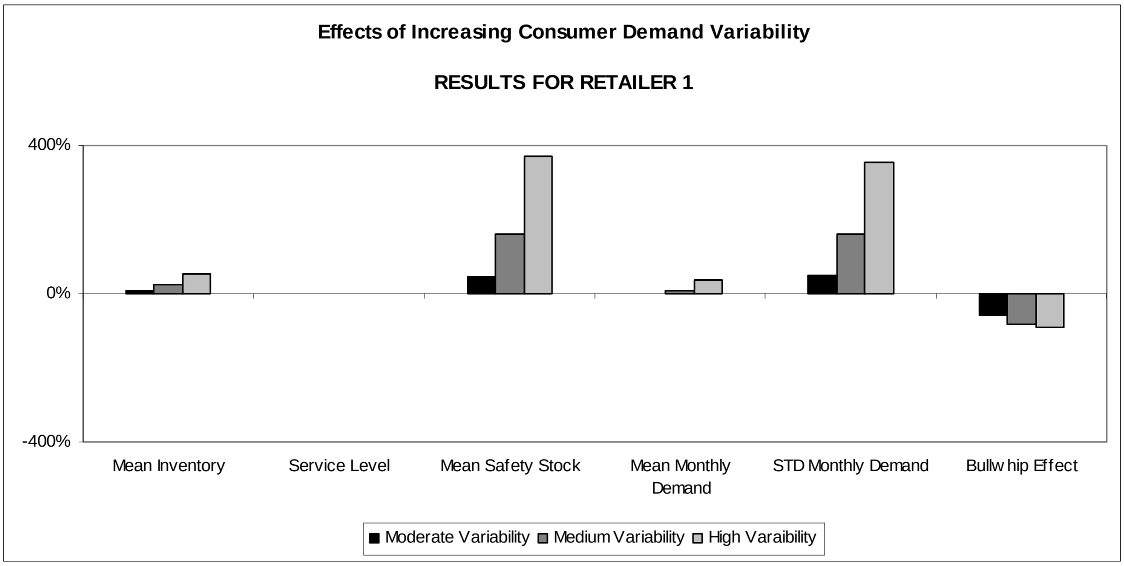

Figure 24: Impact of Higher Consumer Demand Variability for Retailer 1.

As expected, the increase in demand variability leads to a higher standard deviation of monthly demand and thus to increased safety stocks. To provide an almost identical service level, the safety stock under high demand variability is almost 400% higher than in the base model. Consequently, the higher safety stocks lead to a higher mean inventory. In addition, a slight increase of the mean demand may also be observed. This is a result of the truncation of the normal distribution (only nonnegative demand values are generated).

Interestingly, the increase in demand variability leads to a considerably lower bullwhip effect. With a consumer demand distribution of N(30,60), the bullwhip effect is 92% lower compared with the bullwhip effect in the base model. The remarkable decrease in the bullwhip effect is rather surprising since a lower bullwhip effect is often associated with an increase in efficiency throughout the supply chain. Thus, relying solely on the bullwhip effect as a measure of performance is not appropriate since safety stocks and inventory may increase even if the bullwhip effect decreases.

However, changes in the variability of consumer demand do not only affect the output for the retailers. Due to the higher variability of demand, the variability of the order frequency of the retailer also increases. As a consequence, the variability of incoming orders for the upstream company increases too. Figure 25 shows the results for distributor 1. The higher uncertainty has to be compensated with higher safety stocks. To achieve an identical service level, the required safety stock is 38% higher than in the base model. As discussed for the retailers, the bullwhip effect decreases with an increase of demand variability.

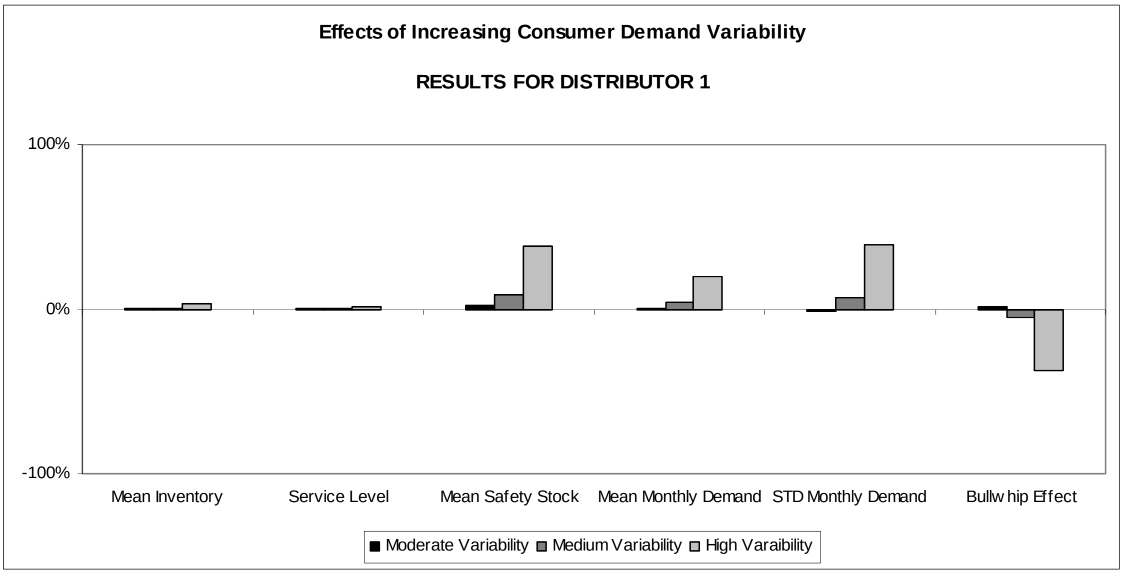

Figure 25: Impact of Higher Consumer Demand Variability for Distributor 1.

The causal relationships resulting from higher consumer demand variability are summarized in Figure 26. The bold arrows between the rectangles emphasize the main effects of an increased variability of the demand.

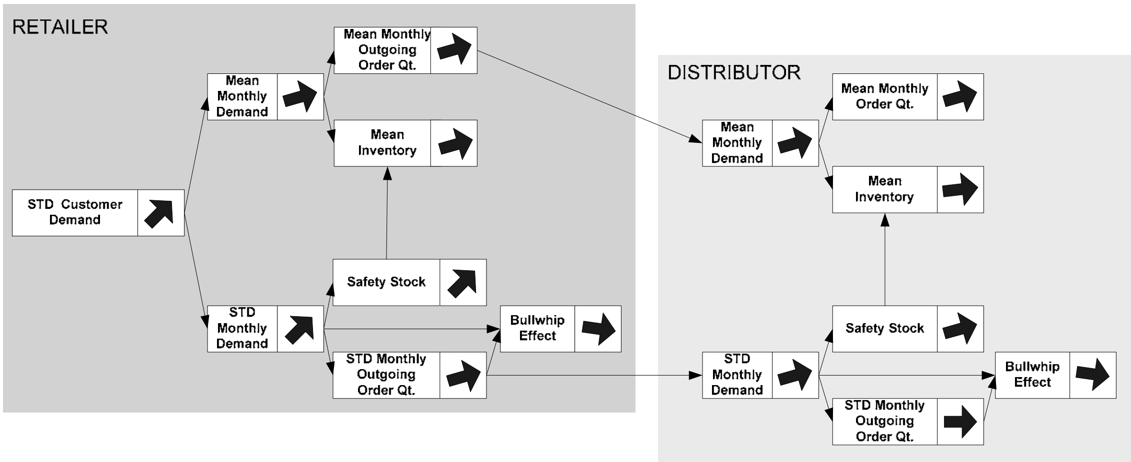

Figure 26: Effects of Higher Consumer Demand Variability (Summary).

As discussed above, the increase in demand variability affects the standard deviation as well as the mean of the monthly demand of the retailers. Due to the higher standard deviation, the variability of the outgoing monthly order quantity increases. However, the increase of the variability of outgoing orders is smaller than that of the incoming demand per month. Hence, the bullwhip effect may be reduced.

The higher mean monthly demand and the higher safety stock both lead to a higher mean inventory. In addition, the higher mean monthly demand leads to a higher monthly outgoing order quantity for the retailer. The changes of the mean and the standard deviation of monthly outgoing order quantities affect the demand for the distributor and may lead to similar effects for the distributor as for the retailer. However, these effects are significantly lower.

5.3. Modification of Order Quantities

To test the impact of modified order quantities, the initial order quantity of 800 for retailer 1 was increased to 1000, 1200, and 1400 units. The expected result of increasing the order quantity should be a higher mean inventory. Figure 27 shows that the inventory increase for retailer 1 is almost proportional to the increase of the order quantity. The service level as well as the mean and the standard deviation of monthly demand are not affected by an increase of the order quantity.

Figure 27: Impact of Higher Order Quantities for Retailer 1.

Even more interesting is the impact of higher order quantities on the bullwhip effect. The order quantities of 1000 and 1200 lead to an increase of the bullwhip effect, whereas the bullwhip effect may be reduced with an order quantity of 1400. Since the standard deviation of monthly demand is not affected by changes to the order quantity, the bullwhip effect is only influenced by the variability of the outgoing order quantity per month. A closer look at the model shows that for all order quantities considered except OQ=1400, retailer 1 places three or four orders per month. By setting an order quantity of 1400 instead, retailer 1 places exactly two orders per month (with a few exceptions). Thus, the variance of outgoing orders is lower and leads to a reduction of the bullwhip effect. Again, using the bullwhip effect alone is not an appropriate measure of the efficiency of a supply chain.

Due to the ambiguous effects on the outgoing order quantity per month, the results for the distributor are not clear. Figure 28 indicates that with higher order quantities placed by the retailer, the standard deviation of monthly demand increases. However, for an order quantity of 1400 units the effects are in the opposite direction.

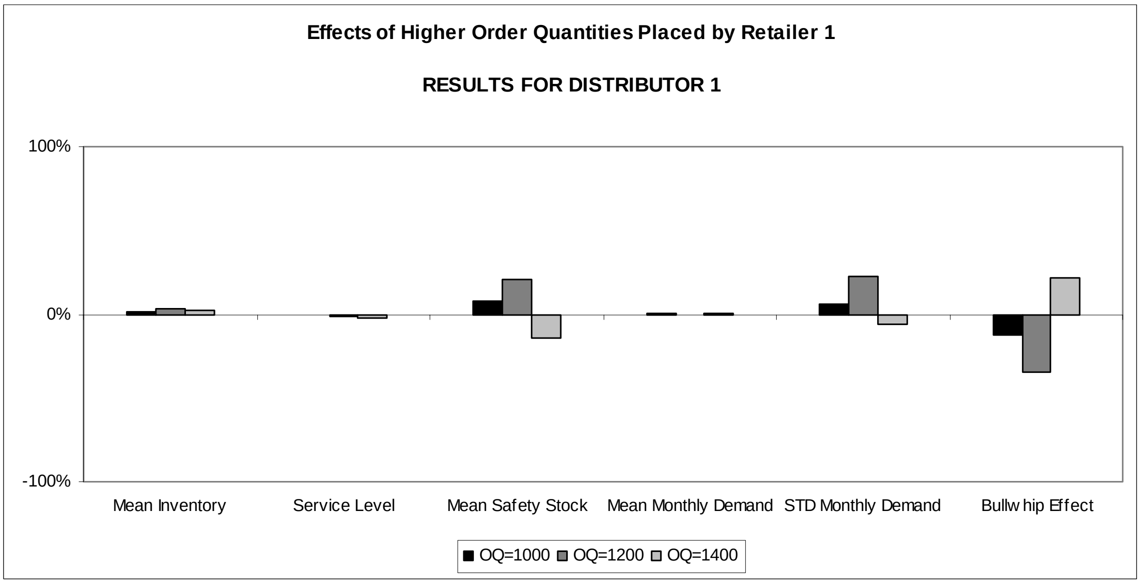

Figure 28: Impact of Higher Order Quantities for the Distributor.

A summary of the causal relationships is shown in Figure 29. Since the effect of the order quantity per month cannot be identified, the effects of larger order quantities for the distributor cannot be determined.

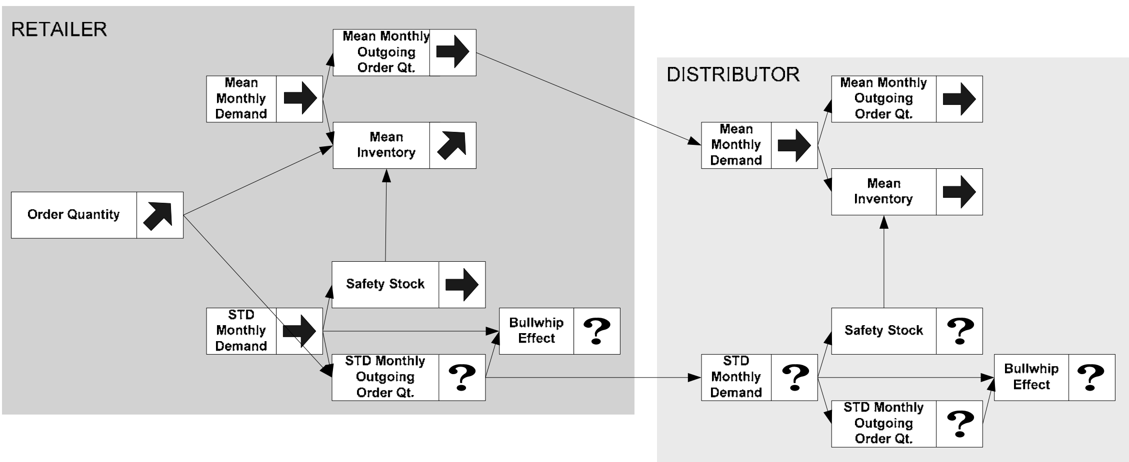

Figure 29: Impact of Higher Order Quantities (Summary).

The experiments presented above show that the results obtained by a simulation model are heavily influenced by the specification of basic model parameters. Due to certain causal relationships, changes of basic model parameters affect not only the output of the focal company but also the performance of upstream supply chain members. For instance, higher consumer demand variability may lead to higher safety stocks for both the retailers and the distributor due to an increase of the variance of outgoing orders placed by the retailers.

In addition, the experiments show that using the bullwhip effect alone to measure output is not sufficient to analyze the performance of a supply chain. Since the bullwhip effect contains information about the variance of both incoming and outgoing orders, it is not easy to identify which measure is affecting the bullwhip effect. Furthermore, the bullwhip effect decreases when demand variability increases. Thus, the lower bullwhip effect would indicate a higher efficiency of the supply chain although the safety stocks rise remarkably due to the higher uncertainty in demand. Hence, for a comprehensive supply chain analysis, multiple output measures have to be considered and the bullwhip effect, at least as defined as ratio of the variances of outgoing and incoming order quantities, should not be overemphasized.

6 LIMITATIONS AND FUTURE RESEARCH

The development of a credible simulation model is a challenging task. Since real world supply chains differ between industries, e.g. the structure of the supply network, the lead times, the inventory control mechanisms or the determination of order quantities, particularly the validation of a simulation model is often not possible. However, the verification procedures applied to the model provide an informative basis that the simulation works as intended.

The output analysis of the base model and the subsequent experiments showed that the simulation model is applicable for comprehensive investigations of supply chains. Of course, the fixing of certain parameters such as lead times or order quantities may be an oversimplification and does not reflect real world situations. In practice, lead times and order quantities may be stochastic variables that vary over time. Since the focus of this paper was the impact of basic model parameters on the performance of the supply chain members, this simplification seemed to be adequate. However, stochastic variables could be considered with only marginal programming effort. Although the experiments presented in the paper are relatively simple, they provide interesting insights into the causal relationships in supply chains. Further development and customization of the model would allow analyses of much higher complexity.

Based on the model presented in the paper, further research could be done. Since inventory control is based on a dynamic reorder point calculation, the output may be analyzed using different demand patterns. For instance, non-stationary demand with trends or seasonal effects could be implemented with little effort. In addition, special emphasis could be placed on the value of shared demand information or the impact of collaboration strategies such as Vendor Managed Inventory could be considered.

7 CONCLUSION

Although numerous simulation studies have been published, the underlying simulation models are often not accessible. As described in this paper, the specification of basic parameters has a significant influence on the derived results. Thus, provision of the simulation model is strongly recommended in order to guarantee the correctness of the results obtained from the model. This would allow a comprehensive verification and validation directly by the simulation user.

The simulation model described in this paper depicts the impact of basic model parameters such as lead times, demand variability, and order quantities on the output of the model. Through certain variations of the inputs, the effects on safety stocks, inventories, and service levels are examined. In addition, the bullwhip effect is computed for every supply chain member as the ratio of the variances of outgoing and incoming orders. The experiments show that using the bullwhip effect as the only measure of supply chain efficiency seems inappropriate since the bullwhip effect may decrease even if the safety stocks and inventories increase. The causal relationships in a supply chain are far more complex than can be investigated simply by analyzing the variances of demand and orders. Furthermore, the computation of the bullwhip effect in supply networks is not an easy task due to conceptual measurement problems of the effect [FrWo00]. Thus, for a comprehensive supply chain analysis, multiple output measures have to be considered for all supply chain members in order to discover the causality of effects.

A critical factor that strongly affects the performance of the supply chain is the ordering frequency of downstream companies. In general, upstream companies order larger quantities than downstream companies. This would lead to decreasing order frequencies as one moves up the supply chain. Since only few orders are placed, there may be a large variation in the monthly order quantity.

The model described in this paper offers a broad area of application. It is applicable primarily to discover the causal relationships in a supply chain. In addition, the model could be further developed with only marginal effort. For instance, the model could be enhanced by information sharing concepts or other collaboration strategies.

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